The concept of buying-shopping disorder: Comparing latent classes with a diagnostic approach for in-store and online shopping in a representative sample in Switzerland

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DOI: https://doi.org/10.1556/2006.2020.00051

diagnostic approach for in-store and online shopping in a representative sample in Switzerland. Journal of Behavioral Addictions, 9(3):808-817.
DOI: https://doi.org/10.1556/2006.2020.00051

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Journal of Behavioral Addictions

DOI:
10.1556/2006.2020.00051

FULL-LENGTH REPORT

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The concept of buying-shopping disorder: Comparing latent classes with a diagnostic approach for in-store and online shopping in a representative sample in Switzerland

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Received: March 24, 2020 • Revised manuscript received: June 8, 2020; August 4, 2020 • Accepted: August 9, 2020

ABSTRACT

Background and aims: Buying-shopping disorder and its transferability to the online sector is controversial. This study investigates in-store and online shopping patterns by comparing data-based modeling to a diagnostic cut-off approach. Further aims were to test model equivalence for gender and identify socio-demographic risk factors. *Methods:* In a representative survey, the Bergen Shopping Addiction Scale (BSAS) was applied, using both an online and in-store version. Latent class analyses were followed by multinomial logistic regression analyses to investigate socio-demographic variables. Measurement invariance across genders was tested with multi-group comparisons. *Results:* With N = 1,012, 3-class solutions provided the best model fit for both in-store and online shopping. Most individuals (76, 86%) were grouped in non-addicted classes, followed by risky (21, 11%) and addicted classes (both 3%). Twenty-eight percent of individuals in the online addicted shopping class remained unidentified using the cut-off. For online shopping, only lower age and education differentiated classes significantly. *Discussion:* Results indicate a close link between online and in-store shopping, albeit with distinguishing features. The cut-off yielded findings discrepant from class probabilities. That buying-shopping disorder mainly affects younger women of lower educational level must be questioned, given the limited associations identified. *Conclusions:* It is important not only to consider different settings of pathological shopping, but also to focus on groups that may not have appeared at risk in previous investigations (e.g., men, older age). The BSAS cut-off warrants further research.

KEYWORDS

shopping-buying disorder, compulsive buying, shopping addiction, Bergen Shopping Addiction Scale, latent class analysis

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INTRODUCTION

Preliminary criteria for buying-shopping disorder include an uncontrollable and excessive urge to buy goods. This leads to significant impairment in social and occupational functioning and can create financial problems (McElroy, Keck, Pope, Smith, & Strakowski, 1994). Initially, the buying process itself initiates feelings of relief. However, this is followed by feelings of regret and guilt due to the uncontrollability of the shopping impulse (Müller et al., 2019).

Pathological buying as a new diagnostic entity is highly controversial. With the official release of the 11th version of the International Classification of Diseases (ICD-11), the condition was grouped in the residual category of other specified impulse control disorders in the ICD-11 Coding Tool (World Health Organization, 2019). This classification scheme has raised concerns because it neglects the condition's phenomenological and etiological similarities with substance use and addictive disorders, including comparable neurobiological and cognitive impairment and shared psychosocial risk factors (Müller et al., 2019). For example, research confirms that cue-related physiological craving also exists in individuals with buying-shopping disorders (Lawrence, Ciorciari, & Kyrios, 2014; Starcke, Antons, Trotzke, & Brand, 2018; Trotzke, Brand, & Starcke, 2017). Moreover, although shopping/buying is initially associated with positive feelings, over the course of development it is increasingly used to provide relief from negative emotional states (Müller et al., 2019). This shift from positive to negative reinforcement aligns with conceptual models of addictive disorders and exceeds its conceptualization as a mere impulse control disorder (Müller et al., 2019; Nicolai, Darancó, & Moshagen, 2016).

Prevalence and risk factors

In one meta-analysis, an overall pooled rate of 4.9% was identified among studies with representative adult samples (Maraz, Griffiths, & Demetrovics, 2016). When incorporating non-representative populations (e.g., university students), estimates were higher for women in the majority of these studies. Age was not found to exert a consistent impact (Maraz et al., 2016). Meanwhile, a Swiss representative survey from 2003 revealed an almost equal rate, of 4.8% (Maag, 2010). In this study, prevalence was almost twice as high among women as in men. In addition, a negative association regarding age was evident, but this did not apply to other socio-demographic variables, like income, educational level, region of residence, employment, and family status (Maag, 2010). In other studies, primarily younger and less-educated women have been found to exhibit an increased vulnerability (Andreassen et al., 2015; Davenport, Houston, & Griffiths, 2012).

Another factor that contributes to the complexity of the concept is the increasing presence of e-commerce, such that online shopping has become a frequently-used alternative to traditional brick-and-mortar stores. This raises questions about the transferability towards the online setting. Some scholars have postulated that pathological online shopping must be understood as a specific subtype of Internet addiction (Brand et al., 2019; Brand, Laier, & Young, 2014; Trotzke, Starcke, Müller, & Brand, 2015). In contrast, in one study with students, pathological online shopping was discovered to be distinct from Internet addiction (Duroy, Gorse, & Lejoyeux, 2014). This is consistent with a network analysis that concluded that "Internet Addiction" is not a tenable construct and that Internet-mediated addictive behaviors should be conceptualized as a spectrum of related, yet distinct disorders (Baggio et al., 2018).

Person-centered approaches

This being said, large-scale empirical investigations specifically assessing pathological online shopping in representative samples are scarce. To date, concepts have mainly been studied within a methodological framework that seeks to identify associations on an aggregate level, employing what is called a variable-centered approach (Granero et al., 2016; Von Eye & Bergman, 2003). On the other hand, empirical clustering techniques offer a more person-centered perspective (Von Eye & Bergman, 2003). In particular, latent variable modeling allows for individuals to be grouped into distinct classes, thereby potentially identifying symptom profiles that are based on shared variable distributions, as opposed to *a-priori* allocation to a diagnostic group based upon a threshold score. Comparing these two approaches can enhance the understanding of mental health conditions (Granero et al., 2016; Von Eye & Bergman, 2003). Mueller et al. (2010) investigated latent profiles in patients with buying-shopping disorder and were able to distinguish between individuals with less versus more severe symptoms and greater comorbidity. Another study revealed the importance of gender, age, functional impairment, and level of education as differentiating factors (Granero et al., 2016). However, in both studies, the populations under investigation were comparably small and limited to clinical samples. Finally, Yi (2013) suggested that three groups should be distinguished: ordinary buyers with low compulsivity and impulsivity, those with excessive impulsivity, and those presenting with both high compulsive and high impulsive buying characteristics. Despite its large-scale approach, the study was not representative of the general population and, to date, latent variable modeling has not been applied in a representative sample. To gain a better understanding of the concept as a potential diagnostic entity, its core features and potential risk factors must be investigated further.

Study aims

The aim of the current study was to examine buying-shopping disorder within a representative sample in Switzerland by comparing a classificatory cut-off approach against latent variable modeling based on symptom endorsement. Specifically, the following research questions were investigated. First, is it possible to differentiate between latent classes that reflect phenomenologically-distinct groups? Second, how do online and in-store shopping patterns compare? Third, how do these latent classes compare to diagnostic classifications based on a threshold score, with respect to prevalence rates and the individuals identified? Fourth, does measurement invariance hold for both men and women? Finally, what other socio-demographic variables are associated with latent buying-shopping patterns?

METHODS

Participants

A representative telephone survey with a target sample size, in excess of N = 1,000, was conducted. Eligibility criteria were living in Switzerland, being above the age of 18 years, and being able to communicate in either French or German. Participation was voluntary and anonymity was ensured. There was no financial or other compensation.

Measures

Socio-demographic variables. Gender, age, language region (French, German), monthly household income (below 4000 CHF; 4001–6000 CHF, 6001–9000 CHF, above 9001 CHF), living area (agglomeration, city, or rural) and highest level of education (low, medium, high) were assessed as potential socio-demographic correlates.

Bergen Shopping Addiction Scale (BSAS). The 7-item Bergen Shopping Addiction Scale (BSAS) (Andreassen et al., 2015) conceptualizes buying-shopping disorder as a behavioral addiction. This is reflected in the assessment of seven addiction-type symptoms (salience, modification of mood, conflict/interference due to shopping, development of tolerance, relapse, feelings of withdrawal, problem-inducing behavior). Participant responses are rated on five-point Likert scales spanning from 0 (“completely disagree”) to 4 (“completely agree”) – so that the sum score ranges from 0 to 28. For each item, a score ≥3 was identified as clinically relevant, per the original coding suggestion. Four of seven items needed to be endorsed for a tentative diagnosis, which reflects a summation score ≥12 (Andreassen et al., 2015), thereby mirroring the diagnostic guidelines for pathological gambling with five out of ten criteria following the DSM-5 (American Psychiatric Association, 2013). Validity of the BSAS has been demonstrated sufficiently. Factorial analyses have demonstrated good construct validity. The scale also correlates well with other measures of buying-shopping disorder. Moreover, it is associated with personality traits and other psychosocial factors known to be associated with buying-shopping disorder (Andreassen et al., 2015). Regarding reliability, Cronbach alpha was in a good range, at 0.87 (Andreassen et al., 2015). For the current study, the BSAS was translated into both German and French. In addition, different versions for both in-store shopping and online shopping were created and presented in a random order. Confirmatory factor analyses for the two translations exhibited fit indices comparable to the original (RMSEA = 0.06–0.09, CFI = 0.96–0.97, TLI = 0.93–0.96). Cronbach alpha was 0.81–0.84 for the German and 0.80–0.84 for the French version. Item-total correlations were all >0.3.

Procedures

The current study was part of a survey, orchestrated by the scientific market research institute gfs-zürich in October 2019. Random stratified sampling was applied using randomly-selected numbers from the telephone book (80% of calls), as well as a random digit dialing procedure for mobile numbers (20% of calls) to reach individuals without phone book listings. Stratification was based on gender, age and language region (French versus German), according to official statistics. The survey averaged roughly 8 min in duration.

Statistical analysis

Analyses were conducted separately for in-store and online shopping. To categorize individuals into latent groups based on dichotomized indicator variables of the BSAS, latent class analyses (LCA) were applied. No parameter constraints were applied, due to the lack of a specific hypothesis concerning this matter. Estimates were based on expectation–maximization. Models with class solutions from one to seven were compared. Lower values of the Bayesian Information Criterion (BIC, Schwarz, 1978) and its adjusted version (Adjusted BIC, Sclove, 1987) indicated a better model fit. In addition, the bootstrap likelihood ratio test (BLRT) was computed (Dziak, Lanza., & Tan, 2014; McLachlan & Peel, 2000): it directly compares two models with differing class numbers. A P-value ≥ 0.05 argues for the selection of the model with fewer classes. According to a simulation study, BLRT and BICs provide the best performance for extracting the correct number of classes for LCAs under different conditions, relative to other indices (Nylund, Asparouhov, & Muthén, 2007) and were, therefore, primarily used to decide class number. For the sake of comprehensiveness, the Akaike Information Criterion (AIC, Akaike, 1974), consistent AIC (cAIC, Bozdogan, 1987), log-likelihood as well as G^2 fit statistics (Collins, Fidler, Wugalter, & Long, 1993), entropy values (Ramaswamy, Desarbo, Reibstein, & Robinson, 1993) and Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT, Lo, Mendell, & Rubin, 2001) also were compared. Entropy was not primarily considered for model selection since classification uncertainty increases by chance with increasing number of latent classes in the model (Masyn, 2013). To test for scalar measurement invariance between men and women, standard LCA procedures were applied (see Kankaraš & Vermunt, 2014). Baseline models were first re-run using gender as a grouping variable and freely estimated parameters. Subsequently, restricted models with constrained parameters across gender were calculated. These models were compared by calculating a likelihood ratio difference test. A non-significant P value indicated no significant difference between models and, thus, measurement invariance (Lanza, Collins, Lemmon, & Schafer, 2007). The same procedure was applied for language region. LCAs and associated analyses were conducted using the statistical software SAS with PROC LCA (Lanza, Dziak, Huang, Wagner, & Collins, 2015) as well as R (R Core Team, 2018).

Finally, multinomial logistic regression models were run to investigate associations between latent classes based upon posterior probabilities and socio-economic variables. All variables were entered simultaneously, with backward selection of variables performed using $P \leq 0.1$ as the criterion for variable inclusion. The continuous predictor (age) was z-standardized. Odds ratios (OR) and associated 95% confidence intervals (CI) were computed. For OR below 1.00, the inverse also was reported.

Ethics

The study was conducted in accordance with the strict legal regulations for conducting research for Swiss survey institutes. By Swiss regulations, no additional ethics approval by a review board was required for this type of survey. All participants were given detailed information about the study and provided informed consent.

RESULTS

Sample characteristics

The final sample consisted of N = 1,012 participants. The estimated maximum sampling error was 3.08%, based on a 95% confidence interval. Mean age was 50.3 years (SD = 17.4), ranging from 18 to 92. Fifty-one percent (N = 514) of the participants were women. The majority lived in the agglomeration of a city in the Swiss German region and reported a monthly household income of either 6001–9000 or more than 9001 Swiss Francs. The most frequent level of education was in the middle range. See Table 1 for details.

Overall, 3.8% (n = 38) of individuals met the cut-off score for in-store shopping and 2.9% (n = 29) for online shopping. Of these 67 participants, 49 (4.8% of the entire sample) met the cut-off for either of the two types of addiction, while 18 (1.8%) met both thresholds.

Latent class analyses

In-store shopping. The favored fit indices (BIC, adjusted BIC, and BLRT) as well as cAIC and LMR-LRT pointed towards a 3-class solution. Consequently, this model was chosen as the final model. Only the AIC favored the 4-class solution and entropy values were highest for the 2-class solution (see Table 2 for details).

Fig. 1 groups 76% of individuals in a class with very low symptom endorsement rates ("non-addicted class"). Twenty-one percent of individuals more strongly endorsed the first two items of the BSAS, while less strongly endorsing the other five items ("risky class"). A third small group of respondents (3%) consistently reported very high propensity of symptom endorsement across almost all items ("addicted class").

Comparing measurement invariance by gender, the freely estimated model, with gender as a grouping variable (G^2 = 171.90, df = 209), did not significantly differ from the restricted model (G^2 = 191.99, df = 230, P = 0.52). Thus, measurement invariance held, providing evidence that the latent classes were similar among both men and women. Language region also exerted no impact on results (P = 0.99).

Online shopping. For online shopping, LCA results were more complex. The BIC together with the cAIC pointed towards a 2-class model. Entropy values were also highest for this solution. In contrast, the adjusted BIC and BLRT favored a 3-class solution. A 4-class solution was preferred

Table 1. Sociodemographic characteristics of the sample

Variable		N (%)
Sex	Male	498 (49.2)
	Female	514 (50.8)
Language	French	255 (25.2)
	German	757 (74.8)
Level of education	Low	83 (8.2)
	Middle	545 (54.4)
	High	373 (37.3)
Household income	≤ 4000 CHF	107 (10.6)
	4001–6000 CHF	171 (16.9)
	6001–9000 CHF	246 (24.3)
	>9001 CHF	312 (30.9)
	No response	176 (17.4)
Living situation	Urban	286 (28.5)
	Agglomeration	367 (36.6)
	Rural	349 (34.8)
		Mean (SD), range
Age		50.3 (17.4), 18–92
Online shopping addiction symptoms		2.49 (3.51), 0–22
In-store shopping addiction symptoms		3.15 (3.81), 0–23

Table 2. Fit indices for the 2–7 latent class models for both online and in-store shopping

	1 class		2 classes		3 classes		4 classes		5 classes		6 classes		7 classes	
	In-store	Online	In-store	Online	In-store	Online	In-store	Online	In-store	Online	In-store	Online	In-store	Online
LL	−2,219.04	−1,769.05	−1,955.55	−1,504.9	−1,919.16	−1,487.23	−1,910.77	−1,477.3	−1,905	−1,470.69	−1,900.58	−1,464.75	−1,895.05	−1,459.86
G^2	702.64	677.02	175.65	148.72	102.87	113.38	86.1	86.1	93.51	80.29	65.71	68.42	54.66	58.64
AIC	716.64	691.02	205.65	178.72	148.87	159.38	**148.1**	**155.51**	155.51	158.29	159.71	162.42	164.66	168.64
BIC	751.06	725.09	279.41	**251.73**	**261.98**	271.31	300.55	306.38	306.38	348.1	390.84	391.17	435.13	436.32
cAIC	758.06	732.09	294.41	**266.73**	**284.98**	294.31	331.55	337.38	337.38	387.1	437.84	438.17	490.13	491.32
Adj. BIC	728.83	702.86	231.77	204.09	**188.93**	**198.27**	202.09	207.93	207.93	224.24	241.56	241.9	260.45	261.64
Entropy	1	1	**0.88**	**0.9**	0.75	0.85	0.75	0.79	0.79	0.79	0.7	0.85	0.71	0.84
BLRT *P*-value	/	/	<0.01	<0.01	**<0.01**	**<0.01**	0.24	0.07	0.50	0.44	0.79	0.39	0.16	0.35
LMR-LRT *P*-value	/	/	<0.001	<0.001	**<0.001**	**<0.001**	0.05	**0.02**	0.19	0.17	0.64	0.14	0.42	0.27

Note. LL = Log-likelihood, Adj. BIC = Adjusted BIC. BLRT = Bootstrapped likelihood-ratio test. LMR-LRT = Lo-Mendell-Rubin adjusted likelihood ratio test. Lowest values of fit indices used for model comparison are printed in bold.

by the AIC and the LMR-LRT. The 3-class solution was selected due to superiority of the BLRT over the LMR-LRT (cf. Nylund et al., 2007) and with respect to theoretical considerations. Similar to in-store shopping, Fig. 2 demonstrates that the majority of individuals (86%) were grouped in a latent class with very low symptom endorsement rates ("non-addicted class"). The second class (11%) encapsulated individuals with high symptom endorsement rates of the first two items of the BSAS and less symptom endorsement of the other five items ("risky class"). And, again similar to in-store shopping, a third class (3%) highly or very highly endorsed all seven symptoms ("addicted class").

Again, measurement invariance by gender held with $G^2 = 162.32$ (df = 286) for the freely estimated model, and $G^2 = 181.24$ (df = 230) for the restricted model, $P = 0.59$. The same applied for language region ($P = 0.10$).

Comparing LCAs and the BSAS cut-off score

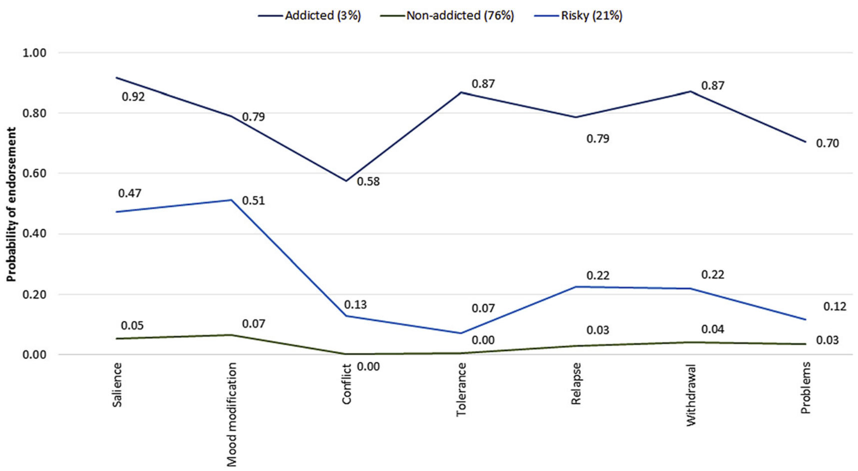
In total, the rate of belonging to one of the two addicted classes was 4.2% ($n = 42$). Seventeen percent of individuals in the online-addicted group were not addicted to in-store shopping, while 24% of online-shopping addicted individuals belonged to the risky in-store class. Likewise, 10 and 33% of in-store addicted individuals were in the non-addicted and risky classes for online shopping, respectively.

Comparing the empirically-identified latent classes and groups identified using the cut-off revealed a high degree of overlap in the non-addicted group for both in-store and online shopping. Regarding in-store shopping, applying the cut-off score identified all individuals in the addicted latent class. However, for online shopping, 28% of individuals in the addicted class were incorrectly classified. Moreover, using the cut-off score, the overall majority (91–94%) of individuals belonging to the risky latent classes for both online and in-store shopping were allocated to the non-addicted group.

Predicting class membership

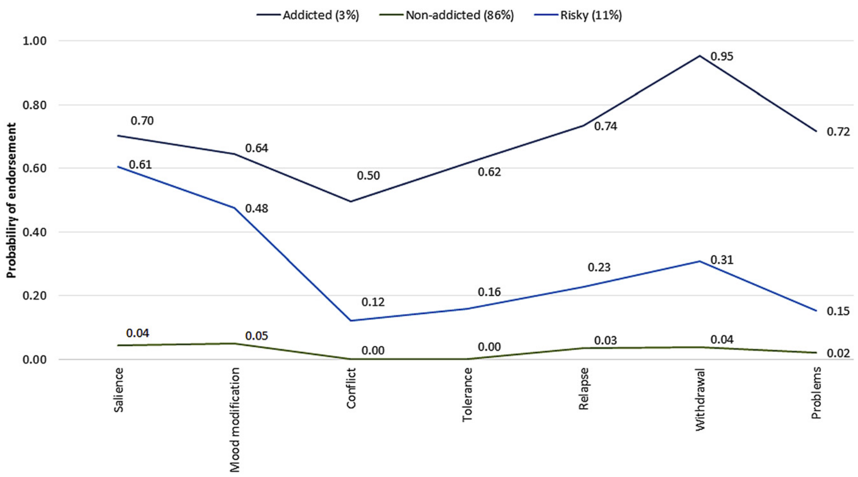
In-store shopping. In the multinomial logistic regression model, higher contributions were related to two non-significant variables: age ($\chi^2(2) = 5.27$, $P = 0.07$) and income ($\chi^2(6) = 12.25$, $P = 0.06$). The overall model failed to reach significance: $\chi^2(8) = 15.31$, $P = 0.05$. Parameter estimates and associated odds ratios are listed in Table 3. For income, changing the odds of being addicted versus not addicted was 4.46–8.49 times more likely among individuals with a monthly household income below 9000 CHF. Regarding age, as it decreased by 1.0 SD, the change in the odds of being addicted versus not in the addicted class was 1.54. Conversely, for the risky versus non-addicted class, no parameter was significant.

Online shopping. The final multinomial logistic regression model was significant with $\chi^2(10) = 26.81$, $P < 0.01$. The variables that remained in the final model were age, level of education (both $P < 0.05$) and living situation ($P = 0.09$).



Note. Values indicate the probability of symptom endorsement for each item.

Fig. 1. Latent class model for in-store shopping



Note. Values indicate the probability of symptom endorsement for each item.

Fig. 2. Latent class model for online shopping

Table 4 lists parameter estimates and associated odds ratios. For the addicted class, the odds of a person with a low level of education being in this versus the non-addicted class were 3.65 times more than for a person with a high level of education. No other variable significantly differentiated addicted from non-addicted individuals.

Regarding risky shopping, a similar effect occurred. The odds of an individual with a medium level of education being in the risky class were 1.96 times less than among individuals with a high level of education. Finally, a one-unit decrease in age was associated with a 1.45 change in the odds of being in the risky versus non-addicted class.

DISCUSSION

To our knowledge, the current study is the first to investigate online and in-store shopping in a representative sample by

Table 3. Results of the multinomial logistic regression model for in-store shopping, all compared to the non-addicted class

Variable	Addicted				Risky		
	OR	95% CI	*P*-value	Inverse OR	OR	95% CI	*P*-value
Age	0.65	0.42–1.00	0.05	1.54	0.87	0.70–1.08	0.21
Income[a]							
≤4000	**8.49**	**2.03–35.47**	**0.003**		1.37	0.72–2.60	0.34
>4–6000	**4.46**	**1.09–18.25**	**0.04**		1.21	0.70–2.08	0.49
>6–9000	**4.62**	**1.25–17.04**	**0.02**		1.03	0.62–1.68	0.92

Note. [a]Reference group is >9000 CHF. OR = Odds Ratio, CI = confidence interval. Significant parameters are printed in bold.

Table 4. Results of the multinomial logistic regression model for online shopping, all compared to the non-addicted class

Variable	Addicted			Risky			
	OR	95% CI	*P-value*	OR	95% CI	*P-value*	Inverse OR
Age	0.76	0.49–1.17	0.21	0.69	**0.53–0.90**	**0.01**	**1.45**
Living situation							
City	1.18	0.44–3.15	0.74	0.66	0.35–1.28	0.22	
Agglomeration	1.07	0.40–2.88	0.89	1.56	0.92–2.65	0.10	
Education							
Low	**3.65**	**1.10–12.08**	**0.03**	0.48	0.17–1.42	0.19	
Middle	1.35	0.53–3.45	0.53	**0.51**	**0.32–0.83**	**0.01**	**1.96**

Note. [a] Reference group is high level of education. OR = Odds Ratio, CI = confidence interval. Significant parameters are printed in bold.

comparing a diagnostic cut-off with an empirical classificatory approach. With respect to the latter, we identified three classes for both shopping methods (in-store and online), with the overall majority of individuals grouped in a non-addicted class. However, 3% were classified as addicted and rates did not differ by shopping method. An additional 11% (online) and 21% (in-store) belonged to a group with risky buying patterns. Regardless of the shopping method, symptoms related to the salience of shopping cues and mood modification were mostly relevant for these classes. Moreover, for the in-store shopping addicted class, cue salience, development of tolerance, and symptoms of withdrawal mattered most, whereas the online shopping addicted class was characterized by high endorsement of the withdrawal symptom. The shift in the relevance of different symptoms between the risky (salience and mood) and addicted classes (salience, tolerance, withdrawal) might be indicative of the transition from positive to negative reinforcement that has been postulated as contributory to the development of buying-shopping disorder (Müller et al., 2019; Müller, Mitchell, & de Zwaan, 2015; Nicolai et al., 2016).

Our findings are generally congruent with the assumption of a conceptual overlap between online and in-store buying-shopping disorder (Lee, Park, & Bryan Lee, 2016). At the same time, they highlight the importance of considering these two entities distinct but closely related mental health conditions, since their symptom endorsement profiles appear slightly different. This is reflected in our finding that up to one third of individuals addicted to one shopping method seemed not to be addicted to the other. This suggests two subtypes of buying-shopping disorder. As such, pathways towards these two problematic shopping patterns also might differ. It is possible that losing control is more easily facilitated during online than in-store shopping, since the ways in which goods can be acquired online extend beyond online-shops, also including the purchase of goods via in-game or in-app options (e.g., King et al., 2019). Accordingly, future research should focus on a more fine-grained analysis of buying modalities within online shopping, depending on the buyers' characteristics.

Comparing empirically-identified latent classes and cut-off-based classification revealed important insights. Whilst overall addiction rates were similar (4.2% versus 4.8%), there was some discrepancy between group allocations determined using LCA versus the cut-off. The latter did not identify almost one third of online addicted individuals and almost all participants with risky buying patterns in the latent classes. Thus, the cut-off score for the BSAS might need adjustment. Yet, this needs to be considered from the perspective that latent class membership is based on probabilities. Moreover, entropy values indicate 15% and 25% likelihoods of false classification of individuals in the selected LCA and cut-off model, respectively. For this reason, further research is warranted.

From an empirical perspective, it is justified to include a third group of individuals at risk to reflect symptom endorsement profiles that were found at the population level. This is also relevant with respect to the implementation of interventions at a public health level. Differentiating individuals based on the dichotomous cut-off might carry the risk of neglecting individuals with risky patterns that might convert to addictive-type buying. Nevertheless, the groups of risky buyers specifically warrant further research. For other behavioral addictions, like gaming disorder, it has been shown that there is a group of highly-involved but non-pathological individuals (Billieu, Flayelle, Rumpf, & Stein, 2019). One cannot exclude the possibility that similar characteristics apply to the risky groups in the current study. Since no other psychosocial factors were measured, any conclusive interpretation in this matter is impossible.

The overall rate of 4.2% of belonging to one of the two addicted classes was comparable to that reported for other countries (c.f., Maraz et al., 2016), as well as for a Swiss investigation that was conducted in 2003 (Maag, 2010). Regarding gender-specific rates, our findings do not support the assumption that women are more vulnerable, instead consistent with the results of a meta-analysis in which gender differences in prevalence rates were not consistently identified in studies with representative populations (Maraz et al., 2016). However, they contrast with those of the previous Swiss investigation (Maag, 2010). At least two explanations for the discrepancy between the two Swiss studies are possible. One is that the discrepancies might reflect methodological bias due to differences in assessments. A second is that rates in the two genders have aligned over the past decade. Consistent findings reported for online buying and selling by the Swiss Addiction Monitoring further fuel the interpretation of a time-specific effect (Marmet, Notari, & Gmel, 2015). To move beyond speculation, future studies must elaborate on gender-specific motivators, various preferences for and functions of buying behaviors, and the online platforms where buying takes place.

The current analyses also partially confirmed the importance of other socio-demographic factors. For in-store shopping, lower age and less income increased a respondent's probability of being assigned to the addicted class. However, since both the predictive model and its coefficients lacked significance, interpretability was severely compromised. Variables not taken into account but found to be relevant in other empirical clustering studies – like personality traits, psychopathological symptoms, and age of disorder onset (Granero et al., 2016) – might play important roles explaining why individuals ended up in specific classes. For online shopping, individuals with lower education were more likely to be in the addicted class, while those with medium compared to high levels of education were more likely to be in the risky class. These findings undermine the importance of education as a risk factor for buying-shopping disorder (Andreassen et al., 2015; Davenport et al., 2012; Granero et al., 2016). A negative association with age was only identified in the risky but not the addicted class, thereby contradicting the findings of both the previously-reported meta-regression model and earlier Swiss survey (Maag, 2010; Maraz et al., 2016). Future research must clarify whether our finding, that there is no association between age and buying-shopping behaviors, is accurate or not. It is also possible that the pathways to risky and addicted shopping differ. Specific cohorts – like digital natives – might have unique vulnerabilities secondary to the increased influence of social media that affect self-perception, social desirability and the sense of belonging to online communities. It remains to be investigated whether these patterns also increasingly apply to older generations or whether their mechanisms for shopping misuse fundamentally differ.

Study limitations

The current study has a number of potential shortcomings. First, since the survey was based on telephone interviews, social desirability bias cannot be excluded; it is possible that participants felt too ashamed to answer truthfully, which could lead to symptoms being underestimated. Second, certain subgroups might have decided not to answer calls from market research institutes. Despite our random stratified sampling approach, this may have affected our sample's representativeness. Third, latent classes were established based upon dichotomized BSAS indicators. One advantage this approach has is being able to identify and group distinct buying patterns. However, other measures of psychopathology or psychosocial factors were not taken into account that might have provided further insights into latent groups. With respect to external validation, this information also would be vital for the determination of alternative cut-off scores. As already discussed, a different interpretation of the risky class as highly involved yet functional is possible. This is also relevant to the comparably-low entropy value of the final in-store LCA model, as well as the non-significant fit of the subsequent logistic regression model, which might again indicate that other variables, which we did not take into account, are important to conceptualizing in-store buying-shopping disorder. Finally, fit indices for the online latent class models did not provide a consistent solution with discrepancies between BLRT and LMR-LRT as well as between BICs and AICs. The current approach of selecting the number of classes based on BLRT and BIC variants might be debatable and further research is warranted to confirm the 3-class perspective of the online shopping construct.

Conclusions

The current study provides important insights into the conceptualization of buying-shopping disorder. Contrary to previous investigations, a data-driven approach was applied to identify individuals at risk. Moreover, we differentiated between online and in-store shopping patterns. Taken together, the characterization of shopping addicts as young, female, and less educated must be questioned, as the impact of gender and socio-demographic variables seems more complex. Finally, it is not only important to consider both online and in-store buying-shopping disorder, but also to identify individuals with risky buying patterns who might gradually develop full-blown addiction.

Funding sources: The study was funded by the Swiss Federal Office of Public Health.

Authors' contribution: MPS designed the study. AW and MA conducted the analysis and wrote the first draft of the manuscript. MA, AM, SH, SA, YK, JB were involved in the interpretation of data and statistical analyses, supervised by MPS. AW, MA and MS have taken responsibility for the integrity and accuracy of data analysis. Funding was obtained by MPS. All authors (MA, AW, SH, SA, YK, JB, MPS) have contributed to the manuscript and approved its final version.

Conflict of interest: There are no conflicts of interest for any of the authors.

Acknowledgements: The authors want to thank Andreas Schaub and Aleksandar Repic from the scientific market research institute gfs-zürich.

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